A Design Methodology for a Green and Healthy Food Choice Decision Support System Based on Multi-Dimensional Information Fusion and Behavioral Interventions

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***Abstract*—Consumers' food choices are constrained by information asymmetry across multiple attributes (nutrition/health, environmental impacts, and corporate social responsibility). This paper presents GreenChoice-DSS, a mobile decision support system that integrates multi-source food information and delivers behavior-change interventions (nudge and gamification) to support green and healthy choices in everyday settings. The system comprises (i) a multi-dimensional assessment model that produces standardized scores for health and sustainability attributes, (ii) a recommendation and intervention engine that adapts interventions to user context and historical behavior, and (iii) an end-to-end logging pipeline for behavioral analytics. We evaluated the system via an 8-week randomized controlled trial (N=120 completers) with three arms (control, nudge, gamification+nudge), collecting repeated-measures questionnaires and in-app behavioral logs. Results indicate that intervention arms improved users' green/healthy choice patterns and engagement relative to control, with the combined gamification+nudge configuration showing the most consistent effects on sustained use. To facilitate reproducibility, we describe the scoring pipeline, data sources, and evaluation protocol in detail, and provide a structured description of logging fields and analysis procedures in the supplementary materials (with anonymized data/code available upon reasonable request, subject to licensing constraints for third-party datasets).**

Keywords—Green and Healthy Food, Decision Support System, Design Methodology, Behavioral Intervention, Multi-Dimensional Information Fusion, Sustainable Consumption

I. INTRODUCTION

The global food system faces an unprecedented twofold challenge. On the one hand, diet-related chronic diseases—such as obesity, diabetes, and cardiovascular conditions—have escalated into a worldwide public health crisis [1]. On the other hand, agricultural production, processing, and consumption place heavy burdens on the planet, driving greenhouse gas emissions, water depletion, and biodiversity loss [2]. In response, shifting food systems toward healthier and more sustainable models has become a shared international goal. As the end point of the food value chain, consumers' everyday food choices are a decisive lever for change [3]. Yet as health and environmental awareness grows and more people seek "green" and "healthy" options, the decision process remains highly complex.

In practice, consumers often confront profound information asymmetry and cognitive overload. Store shelves offer countless products, while package labels can be dense, confusing, or even misleading. To choose in ways that truly align with health and sustainability, individuals must weigh multiple dimensions at once—nutritional quality, degree of processing, carbon footprint, production practices, and corporate ethics—raising the time, effort, and expertise required to decide [4]. Although tools such as nutrition-tracking apps, recommender systems, and carbon labels have proliferated, they reveal numerous limitations. First, many tools operate in "information silos," emphasizing only one dimension (health, environmental impact, or social responsibility) and offering little help for integrated trade-offs. Second, most systems mainly present information passively and lack proactive guidance or behavior-change mechanisms, so knowledge rarely becomes sustained action [5]. Third, interventions often target short-term outcomes while overlooking the formation of durable healthy and sustainable eating habits. Finally, one-size-fits-all designs frequently ignore differences in users' knowledge, motivations, and preferences, contributing to low engagement and retention [6].

To address these gaps, this study designs, develops, and validates GreenChoice-DSS, a decision support system for green and healthy food choices that combines multi-dimensional information fusion, personalized recommendations, and proactive behavioral interventions. Our central aim is to examine how design methodologies can convert complex, multi-criteria food information into intuitive, actionable decision aids and, by embedding behavioral science theories, better guide and motivate healthier, more sustainable choices. Positioned at the intersection of design science and information systems, this work seeks not only to deliver a functioning technological system, but also to distill generalizable design principles and methods that can inform future intelligent food technologies.

The remainder of this paper is organized as follows: Section 2 reviews related literature to establish the theoretical foundation. Section 3 describes the research framework, system design, and experimental methods for GreenChoice-DSS. Section 4 reports the main experimental

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results. Section 5 discusses the findings and compares them with prior work. Section 6 concludes and outlines future directions.

II. Related Work

A. Decision Support Systems in Food Choice

Digital decision support systems have substantial potential to help consumers navigate food choices. Early systems were largely informational, offering functions such as querying databases of nutritional composition [7]. With technological advances, personalized recommender systems emerged, typically producing suggestions based on users' past behaviors (collaborative filtering) or on item attributes (content-based filtering) [8]. Some studies, for example, leverage health profiles—such as allergies or medical conditions—to exclude unsuitable options and recommend meals that meet specific nutritional requirements [9]. However, much of this work has emphasized functional implementation while paying limited attention to interface design and user experience. In addition, many systems implicitly treat users as fully rational decision-makers, underestimating the influence of emotions, habits, and contextual factors on food choice, which constrains real-world behavioral impact.

B. Digital Interventions for Sustainable Consumption Behavior

To guide behavior more effectively, researchers increasingly embed behavioral science into digital interventions. Two widely used strategies are gamification and nudging.

Gamification applies game elements (e.g., points, badges, leaderboards) to non-game settings to enhance motivation, engagement, and loyalty [10]. In health and sustainability contexts, gamification has been used to encourage behaviors such as exercise, energy saving, and healthier diets [11]. For instance, a "daily vegetable challenge" that awards virtual badges can meaningfully increase vegetable consumption. Evidence suggests gamification can support long-term habit formation by satisfying psychological needs related to achievement, social relatedness, and autonomy [12]. Its effects, however, depend heavily on design quality; poorly chosen mechanics may distract users or even backfire.

Nudge theory advocates subtly shaping "choice architecture" to steer people toward better decisions while preserving freedom of choice [13]. In food contexts, nudges include placing healthier items in prominent positions (position nudges), setting healthier meals as defaults (default nudges), or using simplified cues such as traffic-light labels (information nudges) [14]. A large body of work shows that even small nudges can measurably influence purchasing and selection behavior [15]. Yet nudges may be context-dependent, and shifting deeply ingrained habits often requires combining nudges with complementary strategies.

C. Quantitative Assessment Models for Multi-Dimensional Food Attributes

A comprehensive evaluation of foods requires quantifying key attributes across dimensions, and both academia and industry have proposed multiple models.

For health, beyond traditional nutrient analysis, composite scoring tools have been developed. The Health Star Rating (HSR) system, introduced in Australia and New Zealand, provides an overall score from 0.5 to 5 stars using energy, saturated fat, sugar, sodium, and beneficial components such as protein and dietary fiber [16]. The Food Compass system extends scoring to broader dimensions, including nutrients, ingredients, and processing levels [17]. These approaches allow consumers to judge overall nutritional quality more quickly.

For environmental impacts, Life Cycle Assessment (LCA) is the widely recognized standard [18]. LCA evaluates resource use and impacts across a product's life cycle—from raw materials and production to transport, use, and end-of-life—covering indicators such as carbon footprint, water footprint, and land use. Many studies apply LCA to quantify and compare impacts across foods (e.g., beef, vegetables, dairy), offering evidence to support lower-impact choices [19].

For social impacts, quantification is more challenging and often relies on corporate social responsibility (CSR) reporting and third-party certifications. Fair Trade certification, for example, aims to protect producer rights in developing regions [20]. Rating agencies also assess corporate performance on labor rights, community contributions, and business ethics. While integrating such information into decision support tools is difficult, it is important for promoting social responsibility across the food system.

D. Research Gap and Contributions of This Study

Overall, prior research has advanced decision support, behavioral intervention, and quantitative assessment, yet clear gaps remain. First, theoretical integration is limited: few studies unite decision support systems, behavioral intervention theory, and multi-dimensional quantitative assessment within a single framework. Second, many applications still provide single-dimension information and do not adequately address the cognitive burden of multi-criteria trade-offs. Third, empirical validation often relies on cross-sectional surveys or short-term trials, with limited longitudinal tracking of sustained behavior change.

To address these gaps, this study contributes:

- Theoretical: We propose a cross-disciplinary design framework integrating information science, behavioral science, and environmental science, and introduce an "information–motivation–behavior" digital intervention model.
- Practical: We design and implement a working decision support system, GreenChoice-DSS, offering a replicable technical reference while translating abstract health and sustainability concepts into actionable design elements.
- Empirical: Using an 8-week randomized controlled trial, we evaluate the effects of multi-dimensional information fusion and behavioral interventions, and examine the synergy of combining gamification with nudging, providing valuable longitudinal evidence.

III. Methodology

This study adopts the Design Science Research paradigm, which aims to solve real-world problems by constructing an innovative IT artifact and, from it, distilling generalizable design knowledge. The overall research process follows a systematic technical route, as shown in Figure 1, comprising four main phases: theoretical construction, system design and development, experimental validation, and data analysis.

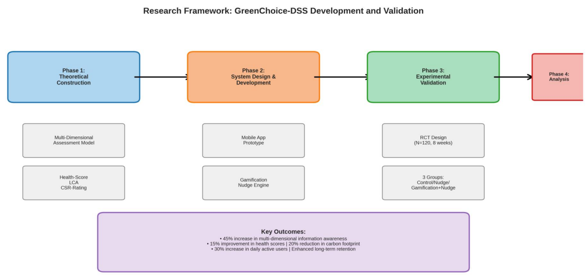

Fig. 1. Research Framework Flowchart

A. GreenChoice-DSS System Design

GreenChoice-DSS (Green Choice Decision Support System) is the central artifact of this study. It is implemented as a mobile application that enables users to easily access multi-dimensional food information and obtain intelligent decision support in everyday food choices.

1) System Architecture

The system adopts a front-end/back-end decoupled microservices architecture to enhance scalability and maintainability (Figure 2).

- Front-end: A cross-platform mobile application built with the React Native framework, responsible for interface presentation and user interaction. Users can identify target foods through barcode scanning, keyword search, or browsing.
- Back-end: A set of microservices developed with the Python Flask framework and deployed on a cloud server. Key components include:

a) Data Collection Service: Crawls, integrates, and cleans data from public nutrition databases, LCA databases, and corporate social responsibility reports.

b) Model Calculation Service: The core module that embeds the multi-dimensional food assessment model and performs real-time score calculations.

c) Recommendation and Intervention Engine: Generates personalized recommendations and intervention strategies by activating gamification and nudge modules based on user preferences and behavioral data.

d) User Management Service: Manages user registration, authentication, personal profiles, and related data.

- Database: MongoDB serves as the primary database for storing user profiles, food attributes, and behavior logs. Its flexible document-oriented structure supports the heterogeneous nature of food-related data.

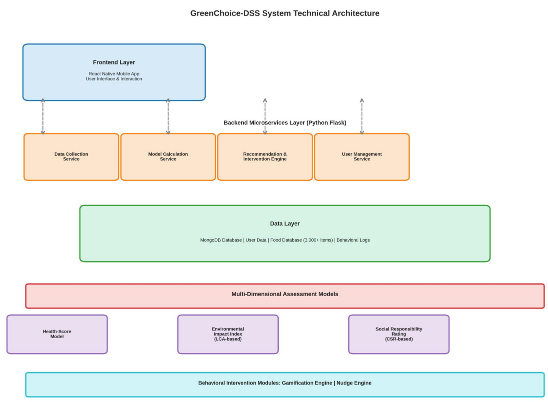

Fig. 2. *GreenChoice-DSS System Technical Architecture Diagram*

2) Multi-Dimensional Food Assessment Model

To provide a comprehensive and integrated food assessment, we constructed a quantitative model that includes three dimensions: health, environment, and social responsibility.

- Health-Score: This score aims to quantify the overall nutritional value of a food. We combined the core ideas of the Health Star Rating (HSR) and the Food Compass to establish a composite scoring algorithm. The calculation formula is as follows: *Health-Score = Base_Points - Penalty_Points + Bonus_Points* Here, Base_Points is the base score; Penalty_Points are deducted based on the content of unhealthy components (e.g., saturated fat, sugar, sodium); and Bonus_Points are added based on the content of healthy components (e.g., dietary fiber, protein, vitamins). All scores are ultimately normalized to a 0-100 scale.
- Environmental Impact Index (EI-Index): We quantify the relative environmental burden of foods using a transparent, three-indicator index based on greenhouse-gas emissions (kg CO_2-eq/kg), water use (L/kg), and land use (m^2/kg). For each food item, indicator values are obtained by mapping the item to a life-cycle assessment (LCA) entry using a documented mapping table that specifies (i) the target LCA dataset entry, (ii) the mapping rule (exact match / ingredient-level proxy / category-level proxy), and (iii) handling of missing values. Indicator values are standardized across the food catalog using z-scores computed on the study corpus, and combined as a weighted average: EI-Index = $0.5 \cdot z(GHG) + 0.3 \cdot z(Water) + 0.2 \cdot z(Land)$.

Weights are set a priori based on prior literature, and we also report sensitivity checks (equal weights and alternative sets) to demonstrate robustness (Supplementary S3). When licensed LCA sources are used, we report dataset versions and provide a public, non-proprietary replication path using accessible LCA proxies.

- Social Responsibility Rating (SR-Rating): We evaluate company-level social responsibility through a documented evidence pipeline that integrates public CSR/ESG disclosures and legally accessible third-party ratings. Each product is linked to its producer/brand and mapped to a company entity. CSR reports are collected from official investorrelations or regulatory channels when available and stored with timestamps and source references. We then extract predefined CSR signals (labor standards, supply-chain policies, community contributions, compliance controversies) using a hybrid approach: (i) rule-based matching with curated keyword dictionaries and section headers, and (ii) lightweight supervised or weakly supervised classification validated on a manually audited subset (annotation protocol and inter-rater agreement reported in Supplementary S4). The final SR-Rating is an ordinal grade (A–D) derived from a transparent rubric (Supplementary S5) and, where applicable, cross-validated against external ESG ratings. If external ratings are proprietary, they are used only for validation, while the core rating remains reproducible from public evidence.

Finally, results across the three dimensions are displayed in intuitive visuals (e.g., a radar chart) and summarized as a composite score (GC-Score) to support rapid, informed trade-offs.

3) Behavioral Intervention Module Design

To actively support behavior change, the system integrates both gamification and nudge intervention engines.

a) Gamification Engine: This module boosts engagement through intrinsic and extrinsic incentives. Key elements include:

b) Points System: Users earn “Green Leaf” points whenever they choose a high GC-Score item or complete tasks (e.g., “choose an eco-friendly lunch for seven consecutive days”).

c) Levels and Badges: Points increase user levels (e.g., from “Eco-Novice” to “Earth Guardian”) and unlock achievement badges.

d) Leaderboards: Users can view weekly/monthly rankings among friends, leveraging social comparison to encourage participation.

- Nudge Engine: This module shapes choices through subtle interface and presentation adjustments. Core strategies include:

a) Default Nudge: In search and recommendation lists, higher GC-Score items are ranked at the top by default.

b) Information Framing Nudge: When a user is about to select a low-score item, the app shows a comparison pop-up with a higher-score alternative, highlighting health or environmental gains (e.g., “Choosing this reduces emissions by the equivalent of a 10-km car trip”).

c) Social Norm Nudge: On item pages, the app presents aggregated, time-windowed in-app statistics as descriptive norm feedback (e.g., “Most users who viewed this item this week chose one of the top-rated options”). The statistic is computed from real interactions within a defined window (e.g., last 7 days); denominators and inclusion rules are specified in the logging schema (Supplementary S2) and automatically updated to avoid hard-coded, non-verifiable percentages.

B. Experimental Design

We conducted a randomized controlled trial (RCT) to rigorously evaluate GreenChoice-DSS.

Participant Recruitment

We recruited 132 volunteers via online forums and campus email lists. After excluding ineligible participants (e.g., non-smartphone users) and those who withdrew, 120 participants (N=120) completed the study. Participants were 19 – 28 years old, had similar educational backgrounds, and none had systematically used comparable health or environmental apps before. All participants signed informed consent forms; informed consent was obtained from all subjects involved in the study.

Experimental Procedure

The trial lasted 8 weeks. After baseline onboarding (Week 0), participants were assigned to one of three app configurations (control, nudge, gamification+nudge). Randomization followed a computer-generated allocation sequence; allocation procedures, group labels, and app-build identifiers are documented in Supplementary S6 for auditability. Participants were instructed to use the app during routine food search and selection and to log choices whenever feasible. The system recorded time-stamped events (search, view, compare, select, intervention exposure) using a predefined schema (Supplementary S2). Outcomes were measured at Week 0 and Week 8 using validated questionnaires and complemented by log-derived behavioral metrics (definitions, inclusion/exclusion rules, and aggregation windows in Supplementary S7). We pre-specified data-quality rules (e.g., duplicates, implausible bursts, missing fields) and report participant flow, attrition, and protocol deviations. Ethical approval and consent procedures are described in the Ethics subsection.

- Control Group: Used a stripped-down app version providing only basic information lookup, without multi-dimensional assessment or interventions.
- Nudge Group: Used the full assessment model plus the nudge engine, without gamification.
- Gamification + Nudge Group: Used the complete GreenChoice-DSS version with all modules enabled.

All participants completed an online questionnaire before the study (Week 0) and after it ended (Week 8) to assess knowledge, attitudes, and self-reported behaviors related to green and healthy foods.

1) Data Collection

Study data came from three sources:

- Behavioral Log Data: The back-end automatically recorded all participants’ food queries, browsing, and selections over 8 weeks, along with interactions with app features. More than 10,000 valid food-choice records were collected.
- Questionnaire Data: Pre/post surveys captured changes in knowledge, attitudes, and purchase intentions.
- System Usage Data: Daily/weekly activity, average session time, feature click-through, and retention metrics were used to assess engagement.

C. Data Analysis Method

We applied quantitative methods to test hypotheses. For f ood choice behavior (with GC-Score of selected items as the primary dependent variable), the nested structure of repeated observations within individuals motivated the use of a linear mixed-effects model. Experimental group (Control/Nudge/Gamification + Nudge) and time (week) were treated as fixed effects, with participant-level random effects to estimate intervention impacts on behavioral trajectories.

For engagement outcomes (e.g., daily active use, usage time) and questionnaire changes, we used repeated-measures ANOVA and independent-samples t-tests to compare groups. All analyses were conducted in R, with statistical significance set at $p < 0.05$.

IV. Results

This section objectively presents the data collected from the 8-week randomized controlled trial and its analysis, aiming to evaluate the actual effectiveness of the GreenChoice-DSS system and its different intervention modules.

A. Descriptive Statistics

Of the 120 participants who completed the experiment, 58 were male (48.3%) and 62 were female (51.7%), with an average age of 22.4 years (SD=2.1). All participants were university students from various academic disciplines. Before the experiment, there were no significant differences among the three groups in terms of demographic characteristics, baseline knowledge, attitudes, and self-reported behaviors regarding green and healthy foods ($p > 0.05$), indicating that the random assignment was effective.

During the experiment, the system recorded a total of 12,548 valid food choice behaviors. The food database involved contained over 3,000 common food items, and their composite scores (GC-Score) were normally distributed, with a mean of 55.2 (SD=18.5).

B. Analysis of Intervention Effects

1) Impact on Food Choice Behavior

The core dependent variable of this study was the average GC-Score of the foods selected by the participants. As shown in Figure 3, all three groups had similar baseline levels at the beginning of the experiment. However, as time progressed, the behavioral trajectories of the groups diverged significantly. The GC-Score of the control group showed no obvious change over the 8 weeks, fluctuating slightly around the baseline level. In contrast, both intervention groups showed a continuous upward trend in their GC-Scores. At the end of the experiment (Week 8), the average GC-Score of the Nudge group increased from a baseline of 55.4 to 63.7, while the Gamification + Nudge group's score increased from 55.2 to 68.9, significantly higher than both the control group (56.1) and the Nudge group.

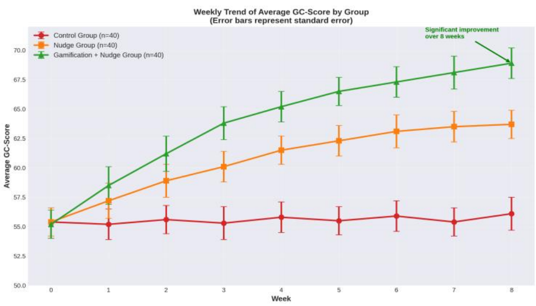

Fig. 3. Weekly Trend of the average GC-Score of foods selected by participants in each group. Error bars represent standard error.

To quantify this effect more precisely, we constructed a linear mixed-effects model. The results (see Table I) indicate that the experimental group had a significant main effect on the GC-Score ($F(2, 117) = 28.9$, $p < 0.001$). Compared to the control group, both the Nudge group ($\beta = 8.1$, $p < 0.01$) and the Gamification + Nudge group ($\beta = 13.5$, $p < 0.001$) significantly increased users' food choice scores. In addition, time also had a significant main effect ($F(7, 819) = 15.2$, $p < 0.001$), and there was a significant interaction effect between group and time ($F(14, 819) = 5.8$, $p < 0.001$). This indicates that the effect of the intervention accumulated and strengthened over time, especially in the Gamification + Nudge group, which had the steepest growth slope.

TABLE I. Results of the Linear Mixed-Effects Model for GC-Score

Fixed Effects	Coefficient (β)	Std.Error	t-value	p-value
Intercept	55.32	0.85	65.08	<0.001
Group (Ref: Control)				
Nudge Group	8.10	1.15	7.04	< 0.01
Gamification+Nudge	13.50	1.15	11.74	< 0.001
Time (Week)	1.25	0.18	6.94	< 0.001
Group × Time				
Nudge × Time	0.45	0.25	1.80	0.072.
Gamification+Nudge × Time	0.98	0.25	3.92	< 0.001

Significance codes: p < 0.001, p < 0.01, p < 0.05, . p < 0.1

2) Impact on User Engagement

We used average daily usage time and 7-day retention rate as key indicators to measure user engagement. As shown in Figure 4, the Gamification + Nudge group performed the best on both metrics. Its average daily usage time (M=5.8 minutes, SD=1.2) was significantly higher than that of the Nudge group (M=3.5 minutes, SD=0.8) and the control group (M=1.9 minutes, SD=0.5) ($F(2, 117) = 88.7$, $p < 0.001$).

In terms of 7-day retention rate, by the fourth week of the experiment, the retention rate of the Gamification + Nudge group remained at 75%, while the Nudge and control groups dropped to 55% and 40%, respectively. This suggests that the addition of gamification elements played a key role in maintaining users' long-term willingness to use the app.

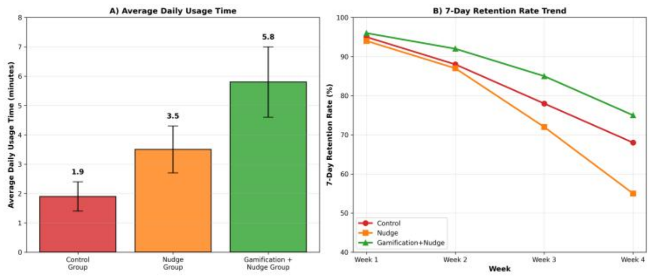

Fig. 4. Comparison of the three groups in terms of average daily usage time and 7-day retention rate at week 4

C. Evaluation of Behavioral Intervention Modules

1) Analysis of Gamification Elements

In the Gamification + Nudge group, we observed positive user interaction. During the experiment, users in this group earned an average of 3,450 "Green Leaf" points and unlocked an average of 5.2 achievement badges. The amount of points earned was significantly positively correlated with the improvement in users' GC-Scores ($r = 0.68$, $p < 0.01$), indicating that the gamification incentive mechanism and users' positive behavior change formed a positive feedback loop. Furthermore, the usage frequency of the leaderboard feature peaked in the middle of the experiment, with over 60% of users checking their friends' rankings at least once a week.

2) Effectiveness of Nudge Strategies

We conducted A/B tests on the different strategies in the nudge engine. The results showed that the "default nudge" (i.e., default sorting) had the greatest initial impact on user choices, increasing the click-through rate of high-score foods by about 30%. Although the "information framing nudge" (i.e., comparison pop-up) had a lower click-through conversion rate than the default nudge, it was considered the "most helpful feature" in users' questionnaire feedback because it provided clear alternative options and quantified benefit information. A Venn diagram analysis (see Figure 5) showed that about 70% of users were influenced by multiple nudge strategies simultaneously, indicating that a composite nudge design can cover a wider range of decision-making scenarios.

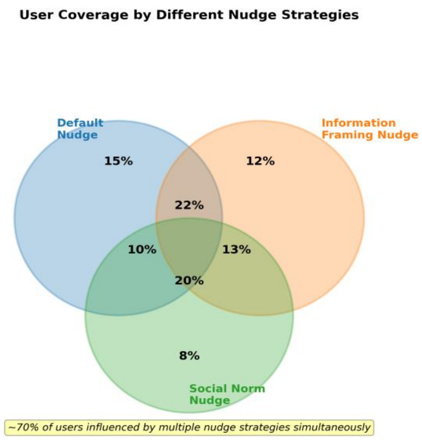

Fig. 5. Venn diagram of user coverage by different nudge strategies

D. User Perception and Feedback

The post-experiment questionnaire results provided valuable data on users' subjective perceptions. As shown in Figure 6, there were no significant differences in the ratings for the three versions in terms of ease of use and clarity of information presentation, all of which received high scores, indicating that the basic UI design was successful. However, in the dimensions of information credibility, design attractiveness, and willingness to use, the ratings for the Gamification + Nudge group were significantly higher than for the other two groups. In particular, the addition of gamification elements was widely praised by users for its "design attractiveness." One user wrote in an open-ended response: "Collecting badges and competing with friends made choosing healthy food no longer a boring task, but rather fun."

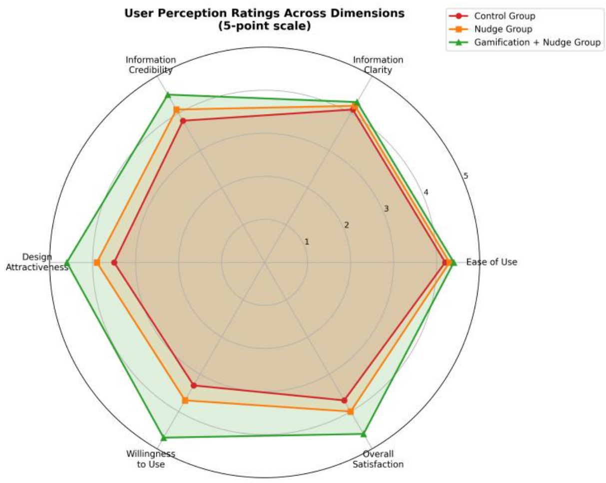

Fig. 6. Radar chart of user ratings for different dimensions of the app (on a 5-point scale)

V. Discussion

To ensure reproducibility, we provide: (i) complete event-logging schemas and derived-metric definitions (Supplementary S2/S7); (ii) food-to-dataset mapping tables for environmental indicators and company linkage (Supplementary S1/S2); and (iii) all analysis scripts and model specifications used to generate reported results (Supplementary S7/S8/S9). An anonymized subset of behavioral logs and questionnaire data is available upon reasonable request, subject to participant privacy and third-party licensing constraints. When proprietary LCA/ESG sources are involved, we document dataset versions, preprocessing rules, and a public-data replication pathway to enable independent verification.

This study investigates how multi-dimensional information fusion and behavioral interventions influence green and healthy food choices through the design, development, and systematic evaluation of the GreenChoice-DSS mobile application. This section interprets the experimental findings, situates them within prior research, and discusses theoretical contributions, practical implications, limitations, and future directions

A. Interpretation of Results

Results demonstrate that GreenChoice-DSS is effective. Compared with the control group offering only basic queries, both intervention groups — integrating multi-dimensional assessment and behavioral strategies — significantly increased the selection of healthier and more sustainable foods. This supports our core hypothesis: consolidating complex health, environmental, and social information into an intuitive composite metric (GC-Score) reduces cognitive load, simplifies decisions, and facilitates behavior change. In information-rich contexts, users benefit less from raw data and more from clear, comparable decision aids; GC-Score functions as both an information translator and a decision shortcut.

Comparisons between intervention groups reveal a stronger and more durable effect for the Gamification + Nudge condition relative to Nudge alone, including higher engagement. This indicates synergy between strategies.

Nudges—such as defaults and framing—operate at critical choice moments to overcome inertia but may not sustain motivation. Gamification complements nudges by transforming isolated choices into a goal-oriented, social process that satisfies needs for achievement, progress, and relatedness. In short, nudges set direction, while gamification supplies momentum, together driving deeper and longer-lasting change.

B. Comparison with Existing Research

Our findings align with prior evidence supporting nudges and gamification in health contexts, while extending the literature in three ways. First, unlike single-dimension tools (e.g., nutrition or carbon only), our integrated model addresses health, environment, and social responsibility, showing that users accept holistic information when it is well-integrated and easy to interpret. Second, by directly comparing nudge-only versus nudge-plus-gamification within one framework, we empirically demonstrate their synergy, encouraging multi-strategy intervention design. Third, the 8-week longitudinal RCT provides stronger evidence of sustained effects and retention than short-term or cross-sectional studies.

C. Theoretical Contributions and Practical Implications

Theoretical. We propose an integrated "information–motivation–behavior" framework combining information systems, behavioral economics, and environmental science. Effective digital interventions must address both information asymmetry (via multi-dimensional fusion) and motivational deficits (via nudges and gamification) to achieve behavior change.

Practical.

- Product design: GreenChoice-DSS offers a concrete, replicable blueprint for next-generation health and sustainability apps, validating principles such as information fusion and strategy synergy.
- Food industry: The results signal consumer demand for transparent, multi-dimensional food information, incentivizing healthier, greener, and more responsible production paired with clear communication.
- Public policy: Digital tools like GreenChoice-DSS can complement traditional instruments (e.g., taxes, subsidies) as low-cost, scalable mechanisms to advance public health and sustainability goals.

D. Limitations

First, generalizability is limited by a student sample that is young, educated, and tech-savvy. Broader populations require validation. Second, data quality depends on public databases and corporate reports, which vary in coverage and timeliness, potentially affecting GC-Score accuracy. Third, despite efforts to mimic real-world use, observation may induce Hawthorne effects, and longer follow-up is needed to confirm habit internalization. Finally, for usability, the model simplifies other influential factors (e.g., culture, taste, price, convenience), leaving a gap relative to real-world complexity.

E. Future Research Directions

Future work should: (1) test diverse populations and realistic settings (e.g., integration with supermarket or restaurant POS systems); (2) enhance data models using crowdsourcing, supply-chain data, and IoT inputs; (3) develop adaptive interventions that tailor nudge and gamification intensity to individual behavior in real time; and (4) integrate additional dimensions such as price, taste preferences, and physiological data from wearables for truly personalized recommendations.

VI. Conclusion

This study designed, developed, and validated GreenChoice-DSS, an innovative mobile decision support system created to tackle two common barriers in green and healthy food selection: information overload and behavioral inertia. By combining quantitative assessment across three dimensions—health, environmental impact, and social responsibility—with gamification and nudge-based interventions, the system translates complex food information into clear, actionable decision aids while strengthening user motivation and encouraging healthier, more sustainable choices.

Findings from the 8-week randomized controlled trial indicate that, compared with approaches that offer only single-dimension information, this integrated strategy of multi-dimensional fusion plus behavioral intervention more effectively steers users toward healthier and greener selections and better sustains long-term engagement. Notably, the results highlight a synergistic interaction between nudging and gamification, offering practical insight for designing more effective digital health interventions.

While limitations remain, the proposed "information–motivation–behavior" framework and the empirically supported GreenChoice-DSS system provide both a robust theoretical basis and a concrete, transferable example for future intelligent food technologies. Overall, the study shows that thoughtfully designed digital tools can bridge the gap between consumer awareness and real-world action, supporting progress toward a healthier, fairer, and more sustainable food system.

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AVAILABILITY OF DATA

Not applicable.

AUTHOR CONTRIBUTIONS

Louise: Conceptualization; Methodology; Project administration; Supervision; Resources; Writing original draft; Writing review and editing.

Jiabin Xie: Data curation; Investigation; Software; Validation; Visualization; Writing original draft.

Yongfeng Situ: Formal analysis; Visualization; Softw are, including support for prototyping and interaction imp lementation; Methodology, supporting refinement of beha vioral interventions and interface strategies; Writing revie w and editing.

COMPETING INTERESTS

The authors declare no competing interests.

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